

Import the required modules

```
In [2]:
        import os
        import math
        import numpy as np
        from scipy.io import loadmat
        import pandas as pd
        import matplotlib.pyplot as plt
        from functools import partial
        from bayes opt import BayesianOptimization
        # Keras modules
        from keras.preprocessing.image import ImageDataGenerator, array to i
        mg, img to array, load img
        from keras.utils import to categorical
        from keras.models import Sequential
        from keras import optimizers
        from keras.layers import Conv2D, MaxPooling2D
        from keras.layers.normalization import BatchNormalization
        from keras.layers import Activation, Dropout, Flatten, Dense
```

/home/poc/anaconda3/lib/python3.6/site-packages/h5py/__init__.py:36:
FutureWarning: Conversion of the second argument of issubdtype from
`float` to `np.floating` is deprecated. In future, it will be treate
d as `np.float64 == np.dtype(float).type`.
 from ._conv import register_converters as _register_converters
Using TensorFlow backend.

Pre-process the Dataset

```
In [3]: # Load the datasets
    sample_full_data = loadmat('Digit_Dataset_Full.mat')
    label_train_data = pd.read_csv("Digit_Dataset_Full_Train_Labels.csv")
    label_test_data = pd.read_csv("Digit_Dataset_Full_Test_Labels.csv")

# Get data from the datasets
    X_train_orig = sample_full_data['Image'][0, 0][0]
    X_test_orig = sample_full_data['Image'][0, 0][1]
```

```
Y train orig = label train data.values[:, 0]
Y test orig = label test data.values[:, 0]
# Print details of the orignal data
print("X train orig shape: " + str(X train orig.shape))
print("X_test_orig shape: " + str(X_test_orig.shape))
print("Y train orig shape: " + str(Y train orig.shape))
print("Y test orig shape: " + str(Y test orig.shape), "\n")
# Reshape the input data for keras
split fraction = 0.9 # should be greater than 0.5
train_set_len = math.ceil((X_train_orig.shape[3] + X_test_orig.shape
[3]) * split fraction)
test set len = X train orig.shape[3] + X test orig.shape[3] - train
set len
X_train = np.zeros((train_set_len, X_train_orig.shape[0], X_train_or
ig.shape[1], X_train_orig.shape[2]))
X test = np.zeros((test set len, X train orig.shape[0], X train orig
.shape[1], X train orig.shape[2]))
Y train = np.zeros((train set len, 1))
Y test = np.zeros((test set len, 1))
# Split into train and test, by the given split fraction
for i in range(train set len + test set len):
    if i < train set len:</pre>
        if i < X train orig.shape[3]:</pre>
            X_train[i] = X_train_orig[:, :, :, i]
            Y train[i] = Y train orig[i]
        else:
            X_train[i] = X_test_orig[:, :, i - X_train_orig.shape
[3]]
            Y train[i] = Y test orig[i - X train orig.shape[3]]
    else:
        if i < X train orig.shape[3]:</pre>
            X_test[i - train_set_len] = X_train_orig[:, :, :, i]
            Y test[i - train set len] = Y train orig[i]
        else:
            X_test[i - train_set_len] = X_test_orig[:, :, :, i - X_t
rain orig.shape[3]]
            Y test[i - train set len] = Y test orig[i - X train orig
.shape[3]]
# Convert the integer lahels into one-hot
```

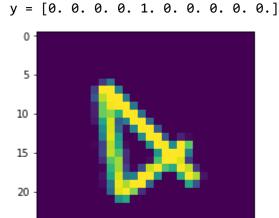
```
\pi convert the integer tubets into one not
Y_train = to_categorical(Y_train, num_classes=10, dtype='float32')
Y test = to categorical(Y test, num classes=10, dtype='float32')
# Print details of the reshaped data
print("X_train shape: " + str(X_train.shape))
print("X_test shape: " + str(X_test.shape))
print("Y_train shape: " + str(Y_train.shape))
print("Y_test shape: " + str(Y_test.shape))
# Create an image generator class
imgGentrain = ImageDataGenerator()
imgGentest = ImageDataGenerator()
train batch = imgGentrain.flow(
    x=X train,
    y=Y train,
    batch size=32,
    shuffle=True,
    seed=1)
test batch = imgGentest.flow(
    x=X_test,
    y=Y test,
    batch size=32,
    shuffle=True,
    seed=2)
X train orig shape: (28, 28, 1, 9000)
X test orig shape: (28, 28, 1, 1000)
Y train orig shape: (9000,)
```

```
X_train_orig shape: (28, 28, 1, 9000)
X_test_orig shape: (28, 28, 1, 1000)
Y_train_orig shape: (9000,)
Y_test_orig shape: (1000,)

X_train shape: (9000, 28, 28, 1)
X_test shape: (1000, 28, 28, 1)
Y_train shape: (9000, 10)
Y_test shape: (1000, 10)
```

Example of an Image

```
In [4]: index = 3600  # just some image for preview
plt.imshow(X_train[index, :, :, 0])
print("y = " + str(np.squeeze(Y_train[index, :])))
```



1.1 - Create a Model (With Batch Normalization)

10

15

20

25

25

```
In [5]: def create model(lr=0.001, beta 1=0.9):
            try:
                del model
             except:
                 pass
             # Create a model
            model = Sequential()
            # Add a convolutional layer
            model.add(Conv2D(filters=32, kernel size=5, strides=(1, 1), padd
        ing='valid', input shape=(28, 28, 1)))
            model.add(BatchNormalization())
            model.add(Activation('relu'))
            model.add(MaxPooling2D(pool size=(2, 2), strides=(2, 2), padding
        ='valid'))
             # 2. Add a convolution layer
            model.add(Conv2D(filters=16, kernel_size=3, strides=(1, 1), padd
        ing='same'))
            model.add(BatchNormalization())
            model.add(Activation('relu'))
            model.add(MaxPooling2D(pool size=(2, 2), strides=(1, 1)))
```

Function to Evaluate the Current Model

```
In [6]: def fit_with(lr=0.001, beta_1=0.9):
    # Create the model using a specified hyperparameters.
    model = create_model(lr=lr, beta_1=beta_1)

# Train the model with the train dataset.
model.fit_generator(
    generator=train_batch,
    steps_per_epoch=len(train_batch),
    epochs=3)

# print the test accuracy
score = model.evaluate(X_test, Y_test, verbose = 0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])

# return the test accuracy
return score[1]

fit_with_partial = partial(fit_with)
```

1.2 - Bayesian Optimization

```
In [7]: # Bounded region of parameter space
```

```
pbounds = {'Ir': (1e-4, 1e-2), 'beta_1': (0.8, 1)}

# Create the bayesian optimizer
optimizer = BayesianOptimization(
    f=fit_with_partial,
    pbounds=pbounds,
    verbose=2, # verbose = 1 prints only when a maximum is observe
d, verbose = 0 is silent
    random_state=1,
)

# Maximize the accuracy
optimizer.maximize(init_points=10, n_iter=10,)

# Print the result
for i, res in enumerate(optimizer.res):
    print("Iteration {}: \n\t{}".format(i, res))

print(optimizer.max)
```

| iter | target | beta_1 | lr |

WARNING:tensorflow:From /home/poc/anaconda3/lib/python3.6/site-packa ges/tensorflow/python/framework/op_def_library.py:263: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be rem oved in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From /home/poc/anaconda3/lib/python3.6/site-packa ges/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflo w.python.ops.math_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.cast instead.

Epoch 1/3

921 - acc: 0.6659

Epoch 2/3

282/282 [============] - 18s 62ms/step - loss: 3.2

720 - acc: 0.7848

Epoch 3/3

819 - acc: 0.8241

Test loss: 0.09564479201845824

```
Test accuracy: 0.971
 1
        0.971
                0.8834
                        0.007231
Epoch 1/3
282/282 [============= ] - 18s 64ms/step - loss: 0.5
866 - acc: 0.8183
Epoch 2/3
282/282 [============= - - 22s 78ms/step - loss: 0.0
882 - acc: 0.9709
Epoch 3/3
282/282 [============= - - 24s 86ms/step - loss: 0.0
131 - acc: 0.9977
Test loss: 0.006796402305364609
Test accuracy: 0.998
                         0.003093
 2
        0.998
                0.8
Epoch 1/3
574 - acc: 0.7941
Epoch 2/3
282/282 [============= - - 25s 89ms/step - loss: 0.0
981 - acc: 0.9802
Epoch 3/3
341 - acc: 0.9960
Test loss: 0.030636158142238856
Test accuracy: 0.995
3
                        | 0.001014 |
       0.995
                0.8294
Epoch 1/3
282/282 [============= - 19s 69ms/step - loss: 0.6
193 - acc: 0.8108
Epoch 2/3
577 - acc: 0.9852
Epoch 3/3
401 - acc: 0.9888
Test loss: 0.009827798534883187
Test accuracy: 0.997
 4
        0.997
                0.8373 | 0.003521 |
Epoch 1/3
282/282 [============= - - 18s 65ms/step - loss: 0.6
721 - acc: 0.8057
Epoch 2/3
282/282 [============= - 16s 55ms/step - loss: 0.0
679 - acc: 0.9792
```

```
Epoch 3/3
282/282 [============= - 15s 52ms/step - loss: 0.0
723 - acc: 0.9778
Test loss: 0.12063172279548598
Test accuracy: 0.963
| 5
        0.963
                  0.8794 | 0.005434
Epoch 1/3
282/282 [============= - 16s 57ms/step - loss: 2.2
387 - acc: 0.7450
Epoch 2/3
282/282 [============= - 15s 52ms/step - loss: 0.0
764 - acc: 0.9764
Epoch 3/3
282/282 [============= - 15s 52ms/step - loss: 0.0
360 - acc: 0.9906
Test loss: 0.03859443750977516
Test accuracy: 0.994
                  0.8838 | 0.006884
 6
        0.994
Epoch 1/3
282/282 [============= - 16s 56ms/step - loss: 1.7
068 - acc: 0.7617
Epoch 2/3
282/282 [============= - 15s 52ms/step - loss: 0.0
918 - acc: 0.9726
Epoch 3/3
282/282 [============= - 15s 53ms/step - loss: 0.0
206 - acc: 0.9945
Test loss: 0.038596218196558764
Test accuracy: 0.991
                  | 0.8409 | 0.008793
1 7
         0.991
Epoch 1/3
717 - acc: 0.8208
Epoch 2/3
282/282 [============= - 19s 67ms/step - loss: 0.0
764 - acc: 0.9751
Epoch 3/3
402 - acc: 0.9876
Test loss: 0.0062416974066291
Test accuracy: 0.998
8
        0.998
                  | 0.8055 | 0.006738 |
Epoch 1/3
```

```
634 - acc: 0.8142
Epoch 2/3
951 - acc: 0.9709
Epoch 3/3
266 - acc: 0.9919
Test loss: 0.02194678747165017
Test accuracy: 0.994
9
      0.994
             0.8835
                  0.005631
Epoch 1/3
977 - acc: 0.8445
Epoch 2/3
648 - acc: 0.9827
Epoch 3/3
497 - acc: 0.9857
Test loss: 0.11759197735682392
Test accuracy: 0.969
             0.8281
                   0.002061
10
      0.969
Epoch 1/3
398 - acc: 0.6154
Epoch 2/3
282/282 [============= - 15s 53ms/step - loss: 0.1
337 - acc: 0.9574
Epoch 3/3
282/282 [============ ] - 15s 53ms/step - loss: 0.0
635 - acc: 0.9792
Test loss: 0.03985049867187627
Test accuracy: 0.987
11
      0.987
            | 0.9238 | 0.01
Epoch 1/3
282/282 [============ - - 16s 58ms/step - loss: nan
- acc: 0.1018
Epoch 2/3
- acc: 0.0987
Epoch 3/3
282/282 [============ - - 15s 53ms/step - loss: nan
- acc: 0.0985
```

```
----
Test loss: nan
Test accuracy: 0.1
12
            1.0
                  0.0001
      0.1
Epoch 1/3
894 - acc: 0.4381
Epoch 2/3
803 - acc: 0.7475
Epoch 3/3
282/282 [============ ] - 15s 54ms/step - loss: 0.5
482 - acc: 0.8516
Test loss: 0.4763501634597778
Test accuracy: 0.886
| 13
     0.886
            0.9575
                  0.0001
Epoch 1/3
713 - acc: 0.4390
Epoch 2/3
282/282 [============ ] - 15s 54ms/step - loss: 0.8
608 - acc: 0.7570
Epoch 3/3
507 - acc: 0.8598
Test loss: 0.45985244297981265
Test accuracy: 0.882
14
      0.882
            0.9061 | 0.0001
Epoch 1/3
459 - acc: 0.4539
Epoch 2/3
536 - acc: 0.7550
Epoch 3/3
326 - acc: 0.8710
Test loss: 0.46304218673706055
Test accuracy: 0.889
| 15
            0.8584
                  0.0001
      0.889
Epoch 1/3
277 - acc: 0.6468
Epoch 2/3
```

```
705 - acc: 0.9496
Epoch 3/3
803 - acc: 0.9768
Test loss: 0.07756807271763683
Test accuracy: 0.964
16
    0.964
          0.9746
              0.01
Epoch 1/3
146 - acc: 0.4450
Epoch 2/3
303 - acc: 0.8924
Epoch 3/3
084 - acc: 0.9678
Test loss: 0.14060125095583498
Test accuracy: 0.956
17
     0.956
          0.9445
               0.01
Epoch 1/3
155 - acc: 0.7216
Epoch 2/3
141 - acc: 0.8757
Epoch 3/3
485 - acc: 0.8889
Test loss: 1.622260201461293
Test accuracy: 0.899
18
     0.899
          0.9013
               0.01
Epoch 1/3
040 - acc: 0.4383
Epoch 2/3
624 - acc: 0.7502
Epoch 3/3
462 - acc: 0.8610
Test loss: 0.4608350868225098
Test accuracy: 0.878
l 19
     0.878
          0.9335
               0.0001
```

```
Epoch 1/3
992 - acc: 0.4848
Epoch 2/3
282/282 [============ ] - 18s 65ms/step - loss: 0.8
468 - acc: 0.7564
Epoch 3/3
337 - acc: 0.8681
Test loss: 0.4637343616485596
Test accuracy: 0.88
  20
             0.88
                       0.9763
                                 0.0001
______
Iteration 0:
      {'target': 0.971, 'params': {'beta_1': 0.8834044009405149,
'lr': 0.007231212485077366}}
Iteration 1:
      {'target': 0.998, 'params': {'beta 1': 0.800022874963469, 'l
r': 0.003093092469055214}}
Iteration 2:
      {'target': 0.995, 'params': {'beta 1': 0.8293511781634226,
'lr': 0.0010141520882110983}}
Iteration 3:
      {'target': 0.997, 'params': {'beta 1': 0.8372520422755342,
'lr': 0.003521051197726173}}
Iteration 4:
      {'target': 0.963, 'params': {'beta 1': 0.879353494846134, 'l
r': 0.005434285666633234}}
Iteration 5:
      {'target': 0.994, 'params': {'beta 1': 0.883838902880659, 'l
r': 0.00688367305392792}}
Iteration 6:
      {'target': 0.991, 'params': {'beta 1': 0.8408904499463035,
'lr': 0.00879336262027036}}
Iteration 7:
      {'target': 0.998, 'params': {'beta 1': 0.8054775186395853,
'lr': 0.0067376283507661824}}
Iteration 8:
       {'target': 0.994, 'params': {'beta 1': 0.8834609604734254,
'lr': 0.005631029301612942}}
Iteration 9:
       {'target': 0.969, 'params': {'beta 1': 0.8280773877190468,
 'lr': 0.0020612047419403}}
```

```
Iteration 10:
       {'target': 0.987, 'params': {'beta 1': 0.9238248606315559,
 'lr': 0.01}}
Iteration 11:
        {'target': 0.1, 'params': {'beta 1': 1.0, 'lr': 0.0001}}
Iteration 12:
        {'target': 0.886, 'params': {'beta 1': 0.9574847719448162,
 'lr': 0.0001}}
Iteration 13:
       {'target': 0.882, 'params': {'beta 1': 0.9060606688478187,
 'lr': 0.0001}}
Iteration 14:
       {'target': 0.889, 'params': {'beta_1': 0.8583786436774691,
 'lr': 0.0001}}
Iteration 15:
        {'target': 0.964, 'params': {'beta 1': 0.974588072127511, 'l
r': 0.01}}
Iteration 16:
       {'target': 0.956, 'params': {'beta 1': 0.9444577517990637,
 'lr': 0.01}}
Iteration 17:
        {'target': 0.899, 'params': {'beta 1': 0.901313725393386, 'l
r': 0.01}}
Iteration 18:
       {'target': 0.878, 'params': {'beta 1': 0.9334773444036866,
 'lr': 0.0001}}
Iteration 19:
        {'target': 0.88, 'params': {'beta 1': 0.9763409771195536, 'l
r': 0.0001}}
{'target': 0.998, 'params': {'beta 1': 0.800022874963469, 'lr': 0.00
3093092469055214}}
```

1.3 - Perform Grid Search

```
In [8]: lr_list = np.array([10**-5, 10**-4, 10**-3])
    mom_list = np.array([0.8, 0.9, 1.0])

    g_grid = np.meshgrid(lr_list, mom_list)
    g_grid_points = np.append(g_grid[0].reshape(-1,1), g_grid[1].reshape
    (-1,1), axis=1)

    g_result_list = []
```

```
for i in g grid points:
  model = create model(lr=i[0], beta 1=i[1])
  model.fit_generator(
    generator=train batch,
    steps_per_epoch=len(train_batch),
    epochs=5)
  score = model.evaluate(X_test, Y_test, verbose = 0)
  g_result_list.append([i[0], i[1], score[0], score[1]])
for i in g result list:
  print("For learning rate = {0} and momentum = {1}: loss = {2}, a
ccuracy = \{3\}".format(i[0], i[1], i[2], i[3]))
Epoch 1/5
378 - acc: 0.1541
Epoch 2/5
100 - acc: 0.2493
Epoch 3/5
855 - acc: 0.3478
Epoch 4/5
913 - acc: 0.4373
Epoch 5/5
242 - acc: 0.5178
Epoch 1/5
936 - acc: 0.4367
Epoch 2/5
455 - acc: 0.7609
```

Epoch 3/5